Aalto University
School of Business

CASH CONVERSION CYCLE'S PREDICTING POWER OVER STOCK RETURNS IN GERMAN STOCK MARKET

Bachelor's Thesis
Florencio Campomanes
Aalto University School of Business
Finance
Summer 2020

Aalto University
School of Business

Author Florencio Campomanes

Title of thesis Cash conversion cycle's predicting power over stock returns in German stock market

Degree Bachelor's Degree

Degree programme Finance

Thesis advisor(s) Michael Ungeheuer

Year of approval 2020 **Number of pages** 19+11 **Language** English

Abstract

In this thesis I study the cash conversion cycle's (CCC) predicting power over cross-sectional stock returns in German stock market between January 1991 and December 2019. I find that the CCC is a significant predictor of future abnormal returns. A portfolio that buys stocks in the lowest CCC decile and shorts stocks in the highest CCC decile earns on average alphas of 5.3- 7.4% per year. The CCC's predicting power remains significant even when controlling for eight previously documented return predictors.

Keywords cash conversions cycle, asset pricing

Contents

1. Introduction

Cash conversion cycle is an accounting measure that shows how long it take for a firm to convert its investment in inventory into cash. More precisely the cash conversion cycle considers the time required for a firm to sell its inventory, the time required to collect its receivables and the time the firm gets to pay its payables. Therefore, the cash conversion cycle captures firm's efficiency in its main operations and working capital management.

Studies on the cash conversion cycle (from now on CCC) measure have proved it to be an interesting measure as it is linked to important characteristics of a firm. E.g. Jose et al. (1996) and Deloof (2003) show that firms with lower CCC are more profitable. Jose et al. (1996) study a twenty-year sample period of U.S. firms and find that firms with lower CCC have higher return on equity (ROE) and return on assets (ROA). Deelof (2003) show that in a sample of 1009 Belgian firms lower CCC is related to higher gross operating income. The cash conversion cycle is also a measure for the firm's need of external financing for working capital (Verlyn et al., 1980 and Raddaz, 2006). Tong and Wei (2011) find that firms that were more dependent on external financing for working capital (i.e. had high CCC) performed worse in the financial crisis of 2007-2009.

The CCC clearly captures important information on firm characteristics like profitability and need of external financing and possible risks from it, but whether this information is fully reflected into the stock prices has been researched only a little so far. Belo and Lin (2012) and Alan et al. (2014) study CCC's key component inventory's relation to stock returns. Belo and Lin (2012) show that firms with higher inventory growth experience lower stock returns. Alan et al. (2014) show that CCC's component, days inventory outstanding, predicts stock returns in the retail industry so that firms with lower days inventory outstanding measure experience higher returns.

Only recently Wang (2019) has suggested CCC as an explanatory variable for cross-sectional stock returns. Wang (2019) studies the CCC's predicting power on U.S. stocks between 1976 and 2015. He finds that returns of firms with lower CCC are on average 4-7% higher per year than returns of firms with high CCC.

Inspired by this recent study by Wang (2019), I study if the CCC's predicting power over stock returns can also be found in another large market, Germany. The previous literature on the

CCC's relation to firm characteristics and CCC's and inventory's inverse relation to stock returns provide me evidence to form the main hypothesis for this thesis: stocks with low CCC experience higher returns than stocks with high CCC. To my best knowledge, this is the first time CCC's predicting power over stock returns is studied in the German stock market.

From sample data between January 1991 to December 2019 I find a significant inverse relation between past CCC and future stock returns. I test the CCC's asset pricing implications by sorting the sample firms into decile portfolios based on CCC and examine the portfolios' excess returns, Fama and French three-factor alphas (Fama and French, 1993) and Carhart four-factor alphas (Carhart, 1997). The difference in excess return and alphas between the lowest CCC portfolio and the Highest CCC portfolio are 0.43-0.60% monthly and are mostly statistically significant. I also test the CCC's asset pricing effect with cross-sectional Fama-Macbeth test (Fama and MacBeth, 1973), controlling for more known return predictors. The results from the cross-sectional regressions are similar to the decile portfolio test.

The rest of my thesis is organized as follows: In section 2 I describe the sample selection, characteristics of the data, and the construction of the main variables. In section 3 I describe the main tests and discuss the results. In section 4 I examine the robustness of the results. In section 5 I conclude.

2. Data

2.1. Sample construction

The cash conversion cycle is expressed in days and consists of three main components: (1) days inventory outstanding (DIO) which measures how many days in average a firm holds its inventory before selling it, (2) days receivables outstanding (DRO) which measures how many days on average does it take for a firm to collect its receivables, and (3) days payables outstanding (DPO) which measures how many days on average does it take for a firm to pay its payables.

I compute the CCC as:

$$CCC = 365 \times \left(\frac{Average\ Inventories - Average\ Accounts\ Payables}{COGS} + \frac{Average\ Accounts\ Receivables}{Revenue}\right) \quad (1)$$

where the three components of the CCC are computed as: DIO = 365 × (Average inventories ÷ COGS), DRO = 365 × (Average Accounts receivables ÷ Revenue), DPO = 365 × (Average Accounts Payables ÷ COGS) (Wang, 2019).

The accounting data for the CCC is from Thomson Reuters Datastream. The average inventories, average accounts receivables and average accounts payable are the average of the beginning of the year and end of the year values. COGS and revenue are the cost of goods sold and the revenue accumulated during the year.

I use annual accounting data and monthly stock return data from Datastream to construct my dataset. I start my sample with all common shares traded in Germany's Deutsche Börse between January 1991 and December 2019. I include both active and delisted stocks to avoid the survivorship bias. I exclude all financial firms which are identified with Standard Industrial Classification (SIC) codes between 6000-6999 and I also exclude secondary listings. The sample consists of firms with available Datastream data for monthly returns, book equity, market capitalization and CCC.

The monthly stock returns and all the stock return based variables are calculated with Datastream Total Return Index (RI), which includes both capital gains and dividends. Ince and Porter (2006) and Schmidt et al. (2011) show that Datastream stock return data and accounting data should be used with caution due to many obvious errors in the data. Similarly to Ince and Porter (2006), I screen the stock return data for static returns caused by static prices after delisting. I winsorize the return data for 0.5% for both tails to eliminate outliers. Similarly to Wang (2019) I exclude firm-year observations in which the revenue divided by the previous year's total assets is lower than 2.5%, to exclude extreme values. To eliminate outliers, I winsorize the CCC and all other accounting variables at 2% level for both tails.

In all main tests, unless mentioned otherwise, I use industry adjusted cash conversion cycle as the measure for CCC. Similarly, to Wang (2019) I adjust the CCC by its industry median since the industry median is less affected by outliers compared to industry average. I use Fama and French 17 industries[1] as industry definitions. The categorization to industries is done with four-digit Standard Industrial Classification (SIC) codes. Firms with missing SIC codes are

[1] Details for the construction of the industries available at Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_17_ind_port.html

excluded from the sample. The final sample consists of 107 977 unique firm-month observations.

The annual accounting data is matched to monthly returns so that the accounting data would have been available to investors before the examined month. Following Fama and French (1992) and Wang (2019) the accounting data from year t is matched to monthly returns of year t + 1 July to year t + 2 June. This way I avoid the look-ahead bias.

2.2. CCC characteristics

I find similar but weaker trend of decreasing average CCC over time in German firms between 1991 and 2019 as Chen et al. (2005) and Wang (2019) find in the average CCC in the U.S. Figure 1 plots the CCC over time. I calculate the average CCC and its components DIO, DRO and DPO for each Fama and French 17 industries. These are reported in Table 1. The average CCC varies considerably between the industries. Drugs, Soaps, Perfumes and Tobacco firms have the highest CCC of 149 days. Transportation firms have the lowest CCC of just 45 days.

Figure 1
The average cash conversion cycle from 1991 to 2019
This figure plots the average cash conversion cycle between the beginning of 1991 and the end of 2019. The horizontal axis is the time and the vertical axis is the average cash conversion cycle (CCC) in days.

Table 1
Average Cash conversion cycle (CCC) by industry.

This table reports the average CCC, DIO, DRO and DPO for each of the Fama and French 17 industries. CCC is the cash conversion cycle, DIO is days inventories outstanding, DRO is days receivables outstanding and DPO is days payables outstanding.

Industry	*CCC*	*DIO*	*DRO*	*DPO*
Drugs, Soap, Perfumes, Tobacco	149	130	83	79
Machinery and Business Equipment	143	108	77	41
Mining and Minerals	116	93	90	55
Fabricated Products	116	85	100	35
Construction and Construction Materials	113	99	57	38
Textiles, Apparel & Footwear	110	89	55	33
Steel Works	105	77	66	37
Automobiles	105	81	56	37
Chemicals	101	78	69	47
Consumer Durables	90	68	59	36
Other	89	62	74	56
Retail Stores	72	68	38	39
Utilities	70	29	79	45
Food	69	56	45	45
Oil and Petroleum Products	65	32	59	44
Transportation	45	46	63	56

2.3. Main variables

The Fama and French three-factor (Fama and French, 1993) data and Carhart's momentum factor (Carhart, 1997) data used in decile portfolio tests is from AQR website[2]. The data for constructing the variables for Fama-MacBeth test (Fama and MacBeth, 1973) is from Datastream.

The control variables used in Fama MacBeth test are: (1) *Beta*, the stock's capital asset pricing model (CAPM) beta calculated following Fama and French (1992). The beta is computed with past 5 years stock returns and with total returns of Germany composite index, requiring that at least 24 months of return data is available. (2) *Size*, the natural logarithm of the firm's market capitalization in the beginning of the month. (3) *B/M*, the firm's book-to-market ratio. The book to market ratio is calculated by dividing the total book value of equity by the total market capitalization. (4) *REV*, the stock return of the previous month t – 1. It is a variable to control the short-term reversal effect (Jegadeesh, 1990). (5) *MOM*, the stocks cumulative return from month t – 12 to month t – 2. It is a variable to control the momentum effect as in Jegadeesh and Titman (1993). (6) *LTRev*, the stocks cumulative return from month t – 60 to month t – 13. It is a variable to control for the long-term reversal effect introduced by De Bondt and Thaler (1985). (7) *AssetGrowth*, the firm's total asset growth from year t – 1 to year t. The asset growth is calculated by dividing the difference of total assets in year t and total assets in year t – 1 by the total assets in year t – 1 as in Cooper et al. (2008). (8) *GrossProfit*, the gross profitability of a firm. The gross profit is calculated as in Novy-Marx (2013) by dividing the difference of revenue in year t and cost of goods sold in year t by the total assets in year t – 1.

3. Main tests and results

3.1. Decile portfolio test

My first test of the CCC's predicting power over stock returns is done with a decile portfolio test. In the decile portfolio test, at the start of each month, from January 1991 to December 2019 I sort the sample stocks into ten decile portfolios based on industry adjusted CCC. The portfolios are constructed so that the first portfolio (Low 1) consists of stocks with the lowest CCC and the 10^{th} portfolio (High 10) consists of stocks with the highest CCC. For each month

[2] The factor dataset is available at: https://www.aqr.com/Insights/Datasets

I calculate the average equally weighted return of each portfolio. With these time series of monthly returns, I calculate the time series average excess return over risk free rate, Fama and French three-factor alpha (Fama and French, 1993) and Carhart four-factor alpha (Carhart, 1997). These time series average excess returns and alphas are reported in percentages in Table 2. In parentheses I report the t-statistics. All t-statistics reported in this thesis are calculated with Newey-West standard errors, which are robust for autocorrelation and heteroscedasticity of the error terms (Newey and West, 1987). In line with my main hypothesis and due to results shown by Wang (2019), I expect the excess returns and alphas to decrease when moving from low CCC portfolio to higher CCC portfolios (i.e. from left to right in Table 2).

The last column of Table 2 shows the corresponding results and Newey-West t-statistics for a Low-minus-High (LMH) zero investment portfolio. This portfolio represents a portfolio that buys the lowest CCC decile stocks and shorts the highest CCC decile stocks. The return of this portfolio is the difference of portfolio 1 and portfolio 10. The last row in Table 2 reports the average CCC for each of the ten portfolios.

The results from this test show that there is no clear monotonic pattern in the excess returns of the ten portfolios. However, comparing the two extreme portfolios, we can see that the Low CCC portfolio clearly outperforms the High CCC portfolio. The CCC spread, i.e. the return of the Low-Minus-High portfolio, is substantial, 0.463% in a month and it is statistically significant on 5 percent level with Newey-West t-statistic of 2.117. The Fama and French three-factor alphas and Carhart four-factor alphas show similar results where there is no clear decreasing monotonic pattern but the differences between the two extreme portfolios are large. The Low-Minus-High portfolio has a statistically significant three factor alpha of 0.597% per month with Newey-West t-statistic of 2.696. Adding the momentum factor decreases the Low-Minus-High portfolio's return and the significance of the results. The four-factor alpha is 0.434% per month and fails to be significant on 5 percent level with Newey-West t-statistic of 1.821.

Overall, the results from the decile portfolio test indicate that the CCC has predicting power over stock returns in the sample period. The economic magnitude of the Low-Minus-High portfolio's excess returns and alphas are substantial and represent 5.3- 7.4% per year. The Low-Minus-High portfolio's excess return and alphas are similar to what Wang (2019) finds for the U.S. stock market. The Low-Minus-High spread seems to be mainly driven by poor performance of the high CCC stocks, since the excess return and three-factor alpha of the highest CCC portfolio are negative and the performance of the lowest CCC portfolio does not particularly stand out. In Figure 2 I plot the excess returns and alphas of the ten portfolios to better illustrate the main results.

Table 2
Decile portfolio test results

In the decile portfolio test each month from January 1991 to December 2019 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.449	0.848	0.513	0.594	0.617	0.449	0.438	0.515	0.223	-0.014	0.463
	(1.369)	(2.022)	(1.675)	(2.065)	(1.958)	(1.47)	(1.486)	(1.763)	(0.709)	(-0.042)	(2.117)
Fama-French three-factor alpha	0.385	0.720	0.347	0.357	0.407	0.220	0.248	0.297	0.057	-0.212	0.597
	(1.530)	(1.994)	(1.844)	(1.971)	(2.117)	(1.092)	(1.303)	(1.569)	(0.264)	(-0.935)	(2.696)
Carhart four-factor alpha	0.670	1.064	0.595	0.658	0.634	0.561	0.498	0.567	0.414	0.236	0.434
	(2.427)	(2.911)	(3.069)	(3.518)	(3.339)	(2.781)	(2.542)	(3.051)	(2.08)	(1.078)	(1.821)
CCC	-84	-48	-31	-17	-3	6	22	44	76	150	

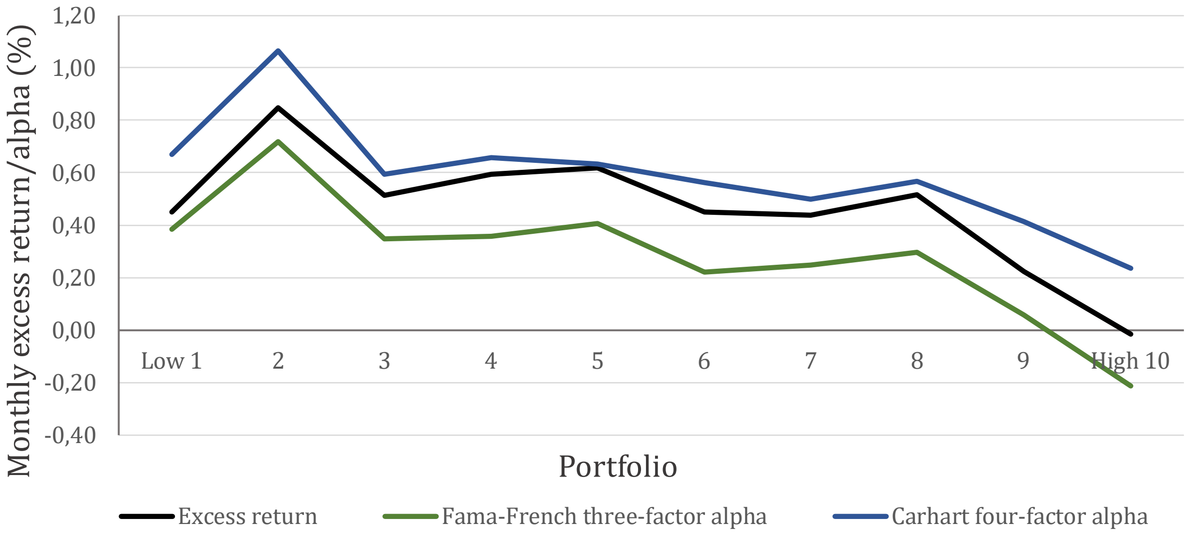

Figure 2
Decile portfolios' excess returns and alphas

In the decile portfolio test each month from January 1991 to December 2019 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This figure plots the time series average excess return, Fama and French three-factor alphas (Fama and French, 1993) and Carhart four-factor alphas (Carhart, 1997) of each decile portfolios. The horizontal axis represents the decile portfolios from 1-10 and the vertical axis is the average monthly excess return/alpha in percentages.

3.2. Fama-MacBeth test

My second main test is a cross-sectional asset-pricing test, Fama-MacBeth test (Fama and MacBeth, 1973). In this test I test if the results of CCC's predicting power from decile portfolio test hold when I control for other return predicting variables. I do the Fama-MacBeth test in three main phases. First, for each month I compute the capital asset pricing model (CAPM) betas and other control variables for every firm as described in Section 2. Next, in each month from January 1991 to December 2019 I run a cross-sectional regression of stock returns (in percentages) on industry adjusted CCC (in years) and control variables. I run a total of four different cross-sectional regressions, adding control variables with each regression. Finally, I report the time series averages of the coefficients from the cross-sectional regressions in Table 3. The Newey-West t-statistics (Newey and West, 1987) are reported in parenthesis. In line with my main hypothesis and due to results shown by Wang (2019), I expect the CCC's coefficient to be negative.

Column 1 of Table 3 shows the results from first regression with CCC as the only explanatory variable specified as:

$$R_{i,t+1} = \alpha_t + \beta_1 \times CCC_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t+1}$ is the realized return of stock i at month t+1, α_t is the intercept, *CCC* is the industry adjusted CCC measured in years and $\varepsilon_{i,t}$, is the error term.

Column 2 shows the results from the second regression specified as:

$$R_{i,t+1} = \alpha_t + \beta_1 \times CCC_{i,t} + \beta_2 \times Beta_{i,t} + \beta_3 \times Size_{i,t} + \beta_4 \times B/M_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where *Beta* is the beta of the stock, *Size* is the natural logarithm of the market capitalization, *B/M* is the book to market ratio.

Column 3 shows the results from the third regression specified as:

$$R_{i,t+1} = \alpha_t + \beta_1 \times CCC_{i,t} + \beta_2 \times Beta_{i,t} + \beta_3 \times Size_{i,t} + \beta_4 \times B/M_{i,t} + \beta_5 \times REV_{i,t} + \beta_6 \times MOM_{i,t} + \beta_7 \times LTRev_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where *REV* is the short-term reversal effect, *MOM* is the momentum effect, and *LTRev* is the long-term reversal effect.

Column 4 shows the results from the fourth regression specified as:

$$R_{i,t+1} = \alpha_t + \beta_1 \times CCC_{i,t} + \beta_2 \times Beta_{i,t} + \beta_3 \times Size_{i,t} + \beta_4 \times B/M_{i,t} + \beta_5 \times REV_{i,t} + \beta_6 \times MOM_{i,t} + \beta_7 \times LTRev_{i,t} + \beta_8 \times AssetGrowth_{i,t} + \beta_9 \times GrossProfit_{i,t} + \varepsilon_{i,t}, \tag{5}$$

where *AssetGrowth* is the total asset growth scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets.

Table 3
Fama-MacBeth test results

In the Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	1	2	3	4
CCC	-0.720	-0.890	-0.998	-0.840
	(-2.836)	(-3.176)	(-2.923)	(-2.732)
Beta		0.028	0.409	0.518
		(0.121)	(1.071)	(1.228)
Size		-0.059	-0.057	-0.063
		(-0.967)	(-0.821)	(-0.827)
B/M		0.058	0.233	0.227
		(2.477)	(2.867)	(2.615)
REV			-0.073	-0.075
			(-5.510)	(-5.227)
MOM			0.011	0.012
			(3.946)	(4.228)
LTRev			0.0001	-0.00002
			(0.167)	(-0.022)
AssetGrowth				-0.670
				(-1.606)
GrossProfit				1.079
				(3.943)
Intercept	0.807	1.840	1.470	1.077
	(2.891)	(1.487)	(1.119)	(0.780)
R^2	0.004	0.048	0.105	0.124

The results from Fama-Macbeth test reported in Table 3 are consistent with the results from the decile portfolio test. In all of the four cross-sectional regressions the CCC has a statistically significant negative coefficient which shows that past CCC has a negative relation with future stock returns. In the first simple regression where the CCC is the only explanatory variable the coefficient of the CCC is -0.72 with Newey-West t-statistic of -2.836. This result is in line with the excess return of Low-Minus-High portfolio in the decile portfolio sort test. The CCC of the Low portfolio is -0.23 in years and the CCC of the High portfolio is 0.411 in years. Therefore, the coefficient of -0.72 suggests a Low-Minus-High return spread of $-0.72 \times (-0.23 - 0.411) = 0.462\%$ per month.

The CCC variable's predicting power holds even when previously documented return predictors are controlled in the other three cross-sectional regressions. Controlling for other return predictors slightly increases the CCC effect. For example, in the fourth regression the CCC's coefficient is -0.84 with Newey-West t-statistic of -2.732. This indicates that CCC effect is not subsumed by other return predictors. In fact, the results from the fourth regression show that CCC is a stronger variable in predicting stock returns than *Beta, Size, B/M, LTRev* and *AssetGrowth* as it obtains higher Newey-West t-statistic. To summarize, the results from my two main tests unanimously show that the CCC's predicting power over stock returns is statistically and economically significant. The results indicate a 0.43-0.60% per month or 5.3 -7.4% per year spread between low CCC and high CCC stocks.

4. Robustness

I perform four different robustness checks to investigate the robustness of the results. In the first robustness check, similarly to Wang (2019) I divide the sample time period into two subperiods and test if the CCC variable has predicting power over stock returns in both subperiods. The first subperiod covers 174 months from January 1991 to June 2005 and the second subperiod covers same amount of 174 months from July 2005 to December 2019. I do the decile portfolio test and the Fama-MacBeth test (Fama and MacBeth, 1973) for both subperiods and report the results in Table 4. For the sake of space, I only report the CCC variable's coefficients, Low-Minus-High portfolio's excess return and alphas and corresponding Newey-West t-statistics (Newey and West 1987) in parenthesis for each robustness check in Table 4. The more comprehensive tables of the results are available in the Appendix.

The results from the first three cross-sectional regressions in the Fama-MacBeth test and from the decile portfolio test show that the magnitude of the CCC variable's effect has been larger in the first subperiod. For example, in the first subperiod the Low-Minus-High portfolio has achieved alphas over two times larger than in the latter subperiod. Although the results from the second subperiod are not significant on 5 percent level. However, when controlling for asset growth and gross profit in the fourth Fama-MacBeth cross-sectional regression a similar difference cannot be found and the CCC's coefficients are very similar in both subperiods. These results from the fourth regression are also not significant on 5 percent level but are significant on 10 percent level. Overall, the results from this subperiod robustness check do not provide enough evidence that the magnitude of the CCC's predicting power would vary between these subperiods.

In the second robustness check, I test whether the main results are robust to the way I construct the CCC measure. I perform the decile portfolio test and Fama-MacBeth test with unadjusted CCC specified in equation (1). The CCC's coefficients from Fama-Macbeth test, Low-Minus-High portfolio's excess returns and alphas from decile portfolio sorts test and Newey-West t-statistics in parenthesis are reported in Table 4. The results from the main tests seem to be robust to the way I construct the CCC measure as the results from this robustness check are mostly similar to the results with industry adjusted CCC.

In the third robustness check, I test whether the CCC effect is present across industries. It could be that the CCC's predicting power is larger for example in more inventory heavy industries. As in Wang (2019) I sort the sample firms into Fama and French five Industries[3]: Consumer Goods, Manufacturing, Hi-Technology, Healthcare, Others. I perform the Fama-MacBeth test for each industry group. I report the CCC's coefficients and Newey-West t-statistics in Table 4. In this test the only results that are significant on a 5 percent level are the coefficients of the fifth "Others" industry. The CCC effect in this industry seems to be somewhat larger than in the whole sample. The results of the other four industries mainly show

[3] Details for the construction of the industries available at Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_5_ind_port.html

that the CCC effect is present since the CCC has a negative relation to stock returns. One big exception to this is the large positive coefficient on the CCC variable in the fourth regression in Healthcare industry. However, results from this robustness check must be interpreted carefully due to mostly lacking statistical significance. I assume that a small sample size in some of the industries decreases the soundness of this robustness check. For example, in most months the Healthcare industry contains no more than 17 firms.

The fourth robustness check tests whether the main results from the decile portfolio test are substantially affected by the way of constructing the Fama and French three-factor (Fama and French, 1993) data and momentum factor (Carhart, 1997) data. I perform the decile portfolio test with two alternative factor datasets. The first one is a factor dataset for Germany constructed by Brückner et al. (2015). The data is available at Humboldt University of Berlin Prof. Richard Stehle's website[4]. The test conducted with this dataset has a slightly shorter sample period, from January 1990 to June 2016 due to availability of data. The second factor dataset is the Fama and French three-factor data and momentum data for European countries from Kenneth French's website[5]. The Low-Minus-High excess returns and alphas and Newey-West t-statistics for both factor sets are reported in Table 4. The main results seem to be robust to the way of constructing the factor data since the results with the two alternative factor data sets are similar to the main results.

[4] Factor dataset available at: https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/daten/fama-french-factors-germany/fama-french-factors-for-germany
[5] Factor dataset available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 4

Robustness check results

This table reports the results of the four robustness checks. The columns 1-4 report the cash conversion cycles' (CCC) time series average coefficient from the four cross-sectional regressions run in the Fama-MacBeth test, specified in equations 2-5. The last three columns report Low-Minus-High portfolio's excess return, Fama and French three-factor alpha (Fama and French, 1993) and Carhart four-factor alpha (Carhart, 1997). The corresponding Newey-West t-statistics (Newey and West, 1987) are reported in parenthesis. The first two rows report the results for two subperiods, before and after June 2005. Row 3 reports results for unadjusted cash conversion cycle measure defined in equation (1). Rows 4-8 report the results for each Fama and French five industries. Rows 9 and 10 report results with different factor data.

	1	2	3	4	Excess Return	Fama-French three-factor alpha	Carhart four-factor alpha
1. Sub period $< 06/2005$	-0.821	-1.002	-1.277	-0.816	0.596	0.892	0.779
	(-2.320)	(-2.818)	(-2.411)	(-1.850)	(1.756)	(3.519)	(2.956)
2. Sub period $> 06/2005$	-0.627	-0.786	-0.738	-0.863	0.338	0.326	0.317
	(-1.676)	(-1.802)	(-1.690)	(-1.894)	(1.148)	(1.078)	(1.086)
3. Unadjusted CCC	-0.582	-0.698	-0.754	-0.620	0.580	0.704	0.493
	(-2.181)	(-2.611)	(-2.725)	(-2.210)	(2.787)	(3.579)	(2.663)
4. Consumer Goods	-0.812	-0.966	-1.562	-1.501			
	(-1.230)	(-1.390)	(-1.409)	(-1.372)			
5. Manufacturing	-1.016	-1.385	-0.372	-0.004			
	(-1.678)	(-1.646)	(-0.550)	(-0.007)			
6. Hi-Technology	-0.201	-0.761	0.048	-1.487			
	(-0.361)	(-1.297)	(0.059)	(-0.681)			
7. Healthcare	-1.055	-1.161	-0.141	4.652			
	(-0.617)	(-0.732)	(-0.061)	(1.254)			
8. Others	-1.117	-1.135	-0.992	-1.289			
	(-2.277)	(-2.732)	(-1.928)	(-2.306)			
9. Humboldt University of Berlin factor data					0.492	0.603	0.502
					(2.030)	(2.575)	(2.002)
10. Fama-French European factor data					0.463	0.615	0.561
					(2.117)	(2.890)	(2.682)

5. Conclusions

In this thesis I study the cash conversion cycle's (CCC) predicting power over stock returns in German stock market. The sample period is from January 1991 to December 2019 and the data consists of 107 977 unique firm-month observations. To test CCC's predicting power I use decile portfolio test and cross-sectional asset-pricing test, Fama-MacBeth test (Fama and MacBeth, 1973). In the decile portfolio test I sort the sample stocks into ten decile portfolios based on CCC and examine the differences in returns between the decile portfolios. In the Fama-MacBeth test I run monthly cross-sectional regressions of stock returns over CCC and control variables.

I find economically and statistically significant results that low CCC stocks outperform high CCC stocks. A portfolio that buys the lowest CCC decile stocks and shorts stocks in the highest CCC decile has on average alphas of 5.3- 7.4% per year. The CCC's predicting power holds even when eight previously documented return predictors are controlled. In addition, I perform several robustness checks and find that the CCC's predicting power is present in two subperiods, 1/1991 - 6/2005 and 7/2005 - 12/2019. The results also show that the CCC's predicting power is robust to the way of measuring CCC and the way of constructing the factor data used for computing the alphas.

My findings provide further evidence of the CCC's predicting power over stock returns by presenting new evidence of the effect's presence in the German stock market. I find that the magnitude of the CCC effect in Germany is similar with the results from U.S. stock market found by Wang (2019). Although I find strong evidence from the full sample, I fail to find significant evidence that the CCC effect is present across industries. To further research the CCC effect in different industries is an interesting topic for future research.

References

Alan, Y., Gao, G. P., & Gaur, V. (2014). Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Science, 60*(10), 2416-2434.

Belo, F., & Lin, X. (2012). The inventory growth spread. *The Review of Financial Studies, 25*(1), 278-313.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*(1), 57-82.

Chen, H., Frank, M. Z., & Wu, O. Q. (2005). What actually happened to the inventories of american companies between 1981 and 2000? *Management Science, 51*(7), 1015-1031.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *The Journal of Finance, 63*(4), 1609-1651.

De Bondt, Werner F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance, 40*(3), 793-805.

Deloof, M. (2003). Does working capital management affect profitability of belgian firms? *Journal of Business Finance & Accounting, 30*(3), 573-588.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607-636.

Ince, O. S., & Porter, R. B. (2006). Individual equity return data from thomson datastream: Handle with care! *Journal of Financial Research, 29*(4), 463-479.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance, 45*(3), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65-91.

Jose, M. L., Lancaster, C., & Stevens, J. L. (1996). Corporate returns and cash conversion cycles. *Journal of Economics and Finance, 20*(1), 33.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703-708.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics, 108*(1), 1-28

Raddatz, C. (2006). Liquidity needs and vulnerability to financial underdevelopment. Journal of Financial Economics, 80(3), 677-722.

Richards, V. D., & Laughlin, E. J. (1980). A cash conversion cycle approach to liquidity analysis. Financial Management, 9(1), 32-38.

Roman Brückner, Patrick Lehmann, Martin H. Schmidt, & Richard Stehle. (2015). *Another german fama/french factor data Set*

Tong, H., & Wei, S. (2011). The composition matters: Capital inflows and liquidity crunch during a global economic crisis. *The Review of Financial Studies, 24*(6), 2023-2052.

Wang, B. (2019). The cash conversion cycle spread. *Journal of Financial Economics, 133*(2), 472-497.

Appendix

Table A1
Decile portfolio test results, robustness check for first subperiod,

In this robustness check decile portfolio test each month from January 1991 to June 2005 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.156	0.290	0.314	0.471	0.399	0.161	0.264	0.322	-0.09	-0.44	0.596
	(0.350)	(0.679)	(0.743)	(1.158)	(0.900)	(0.428)	(0.717)	(0.797)	(-0.182)	(-0.956)	(1.756)
Fama-French three-factor alpha	0.316	0.208	0.326	0.300	0.305	-0.018	0.221	0.269	-0.21)	-0.577	0.892
	(0.966)	(0.600)	(0.993)	(0.991)	(0.890)	(-0.054)	(0.694)	(0.794)	(-0.565)	(-1.560)	(3.519)
Carhart four-factor alpha	0.592	0.541	0.557	0.557	0.493	0.268	0.401	0.477	0.106	-0.186	0.779
	(1.910)	(1.651)	(1.783)	(1.887)	(1.499)	(0.875)	(1.303)	(1.525)	(0.337)	(-0.543)	(2.956)
CCC	-73	-42	-26	-14	-2	6	22	42	72	135	

Table A2

Fama-MacBeth test results, Robustness check: first subperiod

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to June 2005 I run four different cross-sectional regression of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	1	2	3	4
CCC	-0.821	-1.002	-1.277	-0.816
	(-2.32)	(-2.818)	(-2.411)	(-1.850)
Beta		-0.202	0.183	0.279
		(-0.584)	(0.344)	(0.474)
Size		0.049	0.071	0.053
		(0.937)	(1.083)	(0.703)
B/M		0.063	0.391	0.372
		(2.527)	(2.547)	(2.237)
REV			-0.083	-0.088
			(-8.246)	(-8.572)
MOM			0.013	0.014
			(3.479)	(3.409)
LTRev			0.0002	0.00018
			(0.161)	(0.134)
AssetGrowth				-0.791
				(-1.261)
GrossProfit				1.334
				(2.884)
Intercept	0.603	-0.319	-1.151	-1.431
	(1.627)	(-0.289)	(-0.869)	(-1.030)
R^2	0.005	0.06	0.14	0.167

Table A3

Decile portfolio test results, robustness check for second subperiod,

In this robustness check decile portfolio test each month from July 2005 to December 2019 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.722	1.369	0.699	0.709	0.821	0.718	0.601	0.694	0.516	0.384	0.338
	(1.585)	(1.982)	(1.661)	(1.821)	(1.937)	(1.606)	(1.377)	(1.709)	(1.410)	(0.819)	(1.148)
Fama-French three-factor alpha	0.708	1.32	0.719	0.684	0.829	0.788	0.612	0.619	0.536	0.382	0.326
	(1.474)	(1.984)	(1.616)	(1.652)	(1.870)	(1.651)	(1.305)	(1.444)	(1.395)	(0.767)	(1.078)
Carhart four-factor alpha	0.695	1.288	0.688	0.703	0.837	0.791	0.667	0.656	0.527	0.377	0.317
	(1.436)	(1.981)	(1.529)	(1.653)	(1.865)	(1.619)	(1.384)	(1.479)	(1.334)	(0.749)	(1.086)
CCC	-94	-53	-35	-20	-5	6	23	47	81	163	

Table A4

Fama-MacBeth test results, robustness check: second subperiod

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from July 2005 to December 2019 I run four different cross-sectional regression of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	1	2	3	4
CCC	-0.627	-0.786	-0.738	-0.863
	(-1.676)	(-1.802)	(-1.690)	(-1.894)
Beta		0.243	0.621	0.741
		(0.817)	(1.147)	(1.255)
Size		-0.160	-0.177	-0.17
		(-1.506)	(-1.502)	(-1.344)
B/M		0.053	0.086	0.092
		(1.370)	(1.933)	(2.042)
REV			-0.064	-0.062
			(-2.682)	(-2.417)
MOM			0.008	0.009
			(2.150)	(2.558)
LTRev			0.00003	-0.0002
			(0.055)	(-0.262)
AssetGrowth				-0.556
				(-1.038)
GrossProfit				0.842
				(2.814)
Intercept	0.998	3.855	3.917	3.418
	(2.525)	(1.820)	(1.811)	(1.497)
R^2	0.003	0.037	0.071	0.084

Table A5

Decile portfolio test results, robustness check: unadjusted CCC

In this robustness check decile portfolio test each month from January 1991 to December 2019 the sample firms are sorted into ten decile portfolios based on CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.500	0.365	0.859	0.631	0.426	0.672	0.481	0.421	0.373	-0.08	0.58
	(1.707)	(1.276)	(2.067)	(2.003)	(1.422)	(2.256)	(1.667)	(1.265)	(1.214)	(-0.228)	(2.787)
Fama-French three-factor alpha	0.396	0.243	0.664	0.497	0.229	0.479	0.267	0.216	0.154	-0.309	0.704
	(2.144)	(1.346)	(1.866)	(2.098)	(1.175)	(2.503)	(1.403)	(1.034)	(0.762)	(-1.344)	(3.579)
Carhart four-factor alpha	0.652	0.56	0.965	0.754	0.492	0.792	0.514	0.535	0.477	0.16	0.493
	(3.215)	(2.86)	(2.673)	(3.022)	(2.467)	(4.119)	(2.621)	(2.571)	(2.318)	(0.735)	(2.663)
CCC	-8	27	48	65	82	99	118	143	177	247	

Table A6

Fama-MacBeth test results, robustness check: unadjusted CCC

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	0	1	2	3
CCC	-0.582	-0.698	-0.754	-0.62
	(-2.181)	(-2.611)	(-2.725)	(-2.210)
Beta		0.052	0.437	0.513
		(0.228)	(1.126)	(1.224)
Size		-0.058	-0.063	-0.065
		(-0.977)	(-0.914)	(-0.868)
B/M		0.056	0.254	0.233
		(2.363)	(3.162)	(2.882)
REV			-0.073	-0.075
			(-5.485)	(-5.206)
MOM			0.011	0.011
			(3.922)	(4.093)
LTRev			0.0002	0.0002
			(0.265)	(0.200)
AssetGrowth				-0.645
				(-1.550)
GrossProfit				1.076
				(3.980)
Intercept	0.952	1.983	1.748	1.27
	(3.721)	(1.622)	(1.321)	(0.91)
R^2	0.006	0.049	0.105	0.125

Table A7

Fama-MacBeth test results, robustness check: Consumer Goods industry

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression in Consumer Goods industry of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	1	2	3	4
CCC	-0.812	-0.966	-1.562	-1.501
	(-1.230)	(-1.390)	(-1.409)	(-1.372)
Beta		-0.279	0.009	-0.239
		(-0.950)	(0.020)	(-0.456)
Size		0.006	0.064	0.025
		(0.095)	(0.944)	(0.322)
B/M		0.453	0.584	0.412
		(2.082)	(1.892)	(1.054)
REV			-0.039	-0.036
			(-1.961)	(-1.854)
MOM			0.018	0.015
			(2.911)	(1.930)
LTRev			0.003	0.006
			(1.296)	(1.760)
AssetGrowth				-0.083
				(-0.074)
GrossProfit				-1.489
				(-1.516)
Intercept	0.837	0.582	-0.841	0.678
	(2.804)	(0.478)	(-0.604)	(0.389)
R^2	0.031	0.162	0.359	0.441

Table A8

Fama-MacBeth test results, robustness check: Manufacturing industry

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression in Manufacturing industry of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	0	1	2	3
CCC	-1.016	-1.385	-0.372	-0.004
	(-1.678)	(-1.646)	(-0.550)	(-0.007)
Beta		-0.116	0.585	0.805
		(-0.167)	(0.583)	(0.799)
Size		-0.026	-0.100	-0.103
		(-0.134)	(-0.513)	(-0.596)
B/M		0.549	0.267	0.456
		(2.668)	(1.147)	(1.826)
REV			-0.061	-0.054
			(-2.803)	(-2.577)
MOM			0.011	0.013
			(1.790)	(1.873)
LTRev			-0.001	-0.002
			(-0.716)	(-0.575)
AssetGrowth				-1.691
				(-1.570)
GrossProfit				2.811
				(2.787)
Intercept	1.002	1.227	2.522	1.188
	(2.951)	(0.347)	(0.729)	(0.425)
R^2	0.018	0.131	0.273	0.339

Table A9

Fama-MacBeth test results, robustness check: Hi-Technology industry

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression in Hi-technology industry of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	1	2	3	4
CCC	-0.201	-0.761	0.048	-1.487
	(-0.361)	(-1.297)	(0.059)	(-0.681)
Beta		0.14	0.288	0.837
		(0.497)	(0.808)	(1.252)
Size		0.018	0.018	0.095
		(0.370)	(0.284)	(0.951)
B/M		0.311	0.587	0.874
		(2.987)	(2.542)	(2.445)
REV			-0.065	-0.048
			(-3.615)	(-1.881)
MOM			0.009	0.002
			(1.537)	(0.18)
LTRev			0.0003	-0.002
			(0.117)	(-0.885)
AssetGrowth				1.295
				(1.563)
GrossProfit				0.753
				(1.231)
Intercept	0.645	0.003	-0.188	-2.422
	(2.218)	(0.003)	(-0.146)	(-0.985)
R^2	0.026	0.13	0.328	0.387

Table A10

Fama-MacBeth test results, robustness check: Healthcare industry

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression in Healthcare industry of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	0	1	2	3
CCC	-1.055	-1.161	-0.141	4.652
	(-0.617)	(-0.732)	(-0.061)	(1.254)
Beta		-0.451	0.112	1.297
		(-0.798)	(0.160)	(1.239)
Size		-0.234	-0.034	-0.177
		(-1.259)	(-0.258)	(-0.901)
B/M		-0.574	-0.229	-0.278
		(-1.740)	(-0.835)	(-0.906)
REV			-0.044	-0.088
			(-0.888)	(-1.402)
MOM			0.025	0.059
			(1.781)	(3.284)
LTRev			0.003	0.004
			(0.964)	(0.799)
AssetGrowth				0.431
				(0.144)
GrossProfit				1.657
				(1.000)
Intercept	1.291	6.516	1.796	4.062
	(2.978)	(1.606)	(0.679)	(1.003)
R^2	0.08	0.313	0.604	0.76

Table A11

Fama-MacBeth test results, robustness check: "Others" industry

In this robustness check Fama-Macbeth test (Fama and MacBeth, 1973), each month from January 1991 to December 2019 I run four different cross-sectional regression in "Others" industry of stock returns (in percentages) on cash conversion cycle (CCC) and control variables. This table reports the time series averages of the coefficients of the explanatory variables and Newey-West t-statistics for each four regressions. *CCC* is the industry adjusted cash conversion cycle measured in years. *Beta* is the CAPM beta of the stock. *Size* is the natural logarithm of the market capital. *B/M* is the book-to-market ratio. *REV* is the short-term reversal effect. *MOM* is the momentum effect. *LTRev* is the long-term reversal effect. AssetGrowth is the is the total asset growth in one year scaled by lagged total assets and *GrossProfit* is the gross profit scaled by lagged total assets. More detailed descriptions of the variables in Section 2.

	0	1	2	3
CCC	-1.117	-1.135	-0.992	-1.289
	(-2.277)	(-2.732)	(-1.928)	(-2.306)
Beta		0.192	-0.028	-0.142
		(0.590)	(-0.088)	(-0.437)
Size		-0.061	-0.002	0.064
		(-0.661)	(-0.023)	(0.841)
B/M		0.209	0.094	0.093
		(0.985)	(0.493)	(0.468)
REV			-0.076	-0.083
			(-3.180)	(-3.132)
MOM			0.013	0.011
			(3.278)	(2.784)
LTRev			-0.001	-0.001
			(-0.769)	(-0.499)
AssetGrowth				-1.512
				(-1.960)
GrossProfit				0.711
				(1.584)
Intercept	0.765	1.597	0.69	-0.63
	(2.613)	(0.938)	(0.420)	(-0.391)
R^2	0.016	0.093	0.209	0.253

Table A12

Decile portfolio test results, robustness check: Alternative factor dataset by Brückner et al. (2015)

In the decile portfolio test each month from January 1991 to December 2019 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.406	0.545	0.497	0.556	0.648	0.327	0.343	0.484	0.068	-0.085	0.492
	(1.131)	(1.556)	(1.507)	(1.759)	(1.856)	(0.959)	(1.053)	(1.503)	(0.196)	(-0.231)	(2.030)
Fama-French three-factor alpha	0.352	0.407	0.341	0.377	0.455	0.122	0.12	0.278	-0.152	-0.25	0.603
	(1.807)	(2.402)	(2.302)	(2.446)	(2.973)	(0.746)	(0.709)	(1.843)	(-0.927)	(-1.442)	(2.575)
Carhart four-factor alpha	0.440	0.564	0.392	0.472	0.471	0.253	0.196	0.334	-0.04	-0.062	0.502
	(2.151)	(3.173)	(2.972)	(3.048)	(3.303)	(1.596)	(1.241)	(2.351)	(-0.25)	(-0.360)	(2.002)
CCC	-84	-48	-31	-17	-3	6	22	44	76	150	

Table A13

Decile portfolio test results, robustness check: Alternative European factor dataset by Fama and French

In the decile portfolio test each month from January 1991 to December 2019 the sample firms are sorted into ten decile portfolios based on industry adjusted CCC. Each month the average equally weighted return is calculated for each portfolio. This table reports the time series average excess return, Fama and French three factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997) and corresponding Newey-West t-statistics (Newey and West, 1987) for each portfolio. The last column reports the excess return and alphas of Low-Minus-High (LMH) portfolio, which buys the stocks in Low 1 portfolio and shorts stocks in High 10 portfolio. The last row reports the average cash conversion cycle (CCC) for each portfolio.

	Low 1	2	3	4	5	6	7	8	9	High 10	LMH
Excess return	0.452	0.851	0.516	0.597	0.62	0.452	0.441	0.518	0.226	-0.011	0.463
	(1.377)	(2.028)	(1.684)	(2.074)	(1.966)	(1.479)	(1.495)	(1.772)	(0.718)	(-0.033)	(2.117)
Fama-French tree-factor alpha	0.196	0.527	0.163	0.241	0.246	0.09	0.078	0.145	-0.124	-0.419	0.615
	(0.793)	(1.505)	(0.793)	(1.232)	(1.209)	(0.438)	(0.453)	(0.754)	(-0.544)	(-1.772)	(2.890)
Carhart four-factor alpha	0.481	0.82	0.363	0.478	0.392	0.378	0.287	0.358	0.154	-0.08	0.561
	(1.873)	(2.149)	(1.642)	(2.24)	(1.935)	(1.853)	(1.565)	(1.851)	(0.745)	(-0.322)	(2.682)
CCC	-84	-48	-31	-17	-3	6	22	44	76	150	0